A Robust MPC/ISM Hierarchical Multi-Loop Control Scheme for Robot Manipulators

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***Abstract*— In this paper, we propose a robust hierarchical multi-loop control scheme aimed at solving motion control problems for robot manipulators. The kernel of the proposed control scheme is the inverse dynamics-based feedback linearized robotic MIMO system. A first loop is closed relying on an Integral Sliding Mode (ISM) controller, so that matched disturbances and uncertain terms due to unmodelled dynamics, which are not rejected by the inverse dynamics approach, are suitably compensated. An external loop based on Model Predictive Control (MPC) optimizes the evolution of the controlled system in the respect of state and input constraints. The motivation for using ISM, apart from its property of providing robustness to the scheme in front of a significant class of uncertainties, is also given by its capability of enforcing sliding modes of the controlled system since the initial time instant, which is a clear advantage in the considered case, allowing one to solve the model predictive control optimization problem relying on a set of linearized decoupled SISO systems which are not affected by uncertain terms. As a consequence, a standard MPC can be used and the resulting control scheme is characterized by a low computational load with respect to conventional nonlinear robust solutions. The verification and the validation of our proposal have been carried out with satisfactory results in simulation, relying on a model of an industrial robot manipulator with injected noise, to better emulate a realistic set up. Both the model and the noise have been identified on the basis of real data.**

I. Introduction

In several application contexts, including robotics, there is the need to perform particularly critical tasks, while fulfilling some plant constraints, so as to avoid failures or excessive wear of the mechanical or electromechanical parts [1], [2]. Yet, typical industrial robot control approaches, often based on PD or PID controllers [2], fails in guaranteeing this kind of feature. Model Predictive Control (MPC) can represent an appropriate choice to solve this kind of problem, providing an optimal control strategy in case of complex constrained dynamical systems [3], [4], [5], [6], [7], [8]. In past years, the MPC approach has been efficiently used in several industrial processes, such as chemical plants or oil refineries [9], but its application to robotic systems in a true industrial environment in which disturbances affect the robotic system to control and the model of the robot is inevitably inaccurate is still limited.

Indeed, the classical MPC approach is based on the knowledge of the dynamical model of the system, according to which the optimal control law is determined starting from the prediction of the future values of the state variables.

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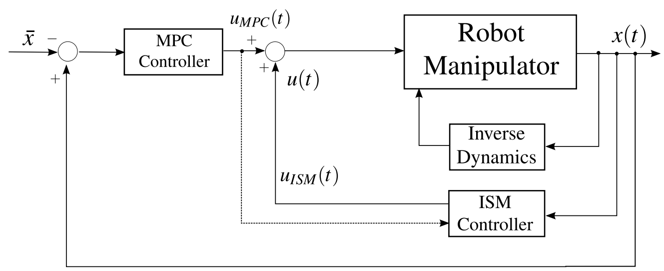

Fig. 1. Scheme of the overall hierarchical multi-loop control scheme for robot manipulators.

Recent developments are oriented to ensure robustness of the controlled system in front of possible modelling uncertainties or external disturbances, while satisfying the system constraints [10], [11], [12]. In this direction, the two main approaches, developed in the last years, are the so-called min-max approach, able to fulfill the plant constraints considering the worst possible uncertainty realization, but at the price of a very high computational burden [13], [14], [15], and the so-called open-loop nominal approach, where the real constraints are shrunk to guarantee that the original constraints are fulfilled for any possible uncertainty realization [16], [17], [18]. In this paper, with reference to the class of robot manipulators, and having the aim of keeping the computational complexity to a minimum, in order to make the proposal really usable in practice, an alternative optimal control scheme is presented. Inspired by the open-loop nominal approach and by [19], we propose a robust hierarchical multi-loop control scheme (Fig. 1). More precisely, the scheme consists of three loops: an inner loop based on the well-known Inverse Dynamics approach [2], oriented to transform the nonlinear MIMO robotic system into a set of perturbed linearized decoupled SISO systems (the number of systems is equal to the number of joints of the robot manipulator); a second loop involving a controller designed according to the so-called Integral Sliding Mode (ISM) control approach [20], which has the task of performing the rejection of all the matched uncertainties (see [21], for a definition of this class of uncertain terms); finally, an external loop where a controller of MPC type has the role to optimize the evolution of the controlled system in the respect of state and input constraints. By the virtue of the linearizing and decoupling properties of the Inverse Dynamics based inner loop, and of the capability of the ISM controller to make the controlled system insensitive to matched uncertainties since the initial time instant, it is possible to rely on the standard linear MPC methodology [6] to design the controller of the outer loop, with a clear benefit in terms of containment of computational complexity.

The present paper is organized as follows. In Section II, the considered robotic system is described, and kinematical and dynamical aspects are reviewed. In Section III, the control problem to solve is formulated and the Inverse Dynamics approach is described. In Section IV, the proposed control scheme is discussed, illustrating the ISM controller and the MPC control law. Section V is devoted to present simulation results obtained by relying on the model of an industrial manipulator, a COMAU SMART3-S2 anthropomorphic robot. Both the model and the noise used in simulation have been identified on the basis of experimental tests [22], so that the simulation environment is quite realistic.

II. The Robot Model

The robotic system we are dealing with is a 6-joint robot manipulator, and, in order to formulate the model of the robot, kinematical and dynamical aspects have to be recalled. For the

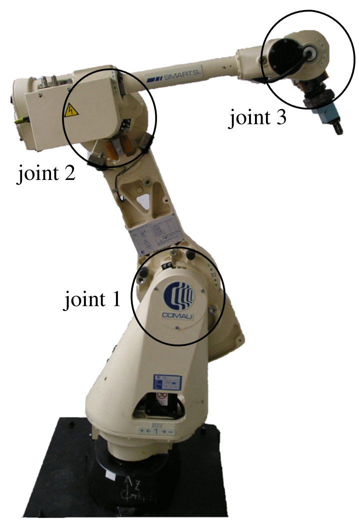

Fig. 2. The COMAU SMART3-S2 anthropomorphic industrial robot manipulator with the joints numeration.

sake of simplicity, we consider only vertical planar motions of the robotic manipulator, locking three of the six joints of the robot, as indicated in Fig. 2. However, the proposed control scheme and the design of the controllers could have a more general validity, even for n-joint spatial robot manipulators.

Let $l_i,\ i=1,2,3$, denote the length of the i-th link, $q_1$denote the orientation of the first link with respect to y-axis clockwise positive, and $q_j,\ j=2,3$, denote the displacement of the j-th link with respect to the $(j-1)$-th one clockwise positive. Let $O-\{x,y,z\}$ denote the base-frame of the robotic manipulator, and $O_e-\{n,s,a\}$ denote the end-effector frame, as indicated in Fig. 3.

A. Kinematics

The kinematics of a 3-joints manipulator, which describes the relationship between the joint variables $q=[q_1\ q_2\ q_3]^T$ and the end-effector position and orientation $x=[p_x\ p_y\ \phi]^T$ in the planar workspace, with reference to Fig. 3, can be written as

$$\begin{cases} p_x = -l_1\sin(q_1) - l_2\sin(q_1+q_2) - l_3\sin(\phi) \\ p_y = l_1\cos(q_1) + l_2\cos(q_1+q_2) + l_3\cos(\phi) \\ \phi = q_1+q_2+q_3 \end{cases} \tag{1}$$

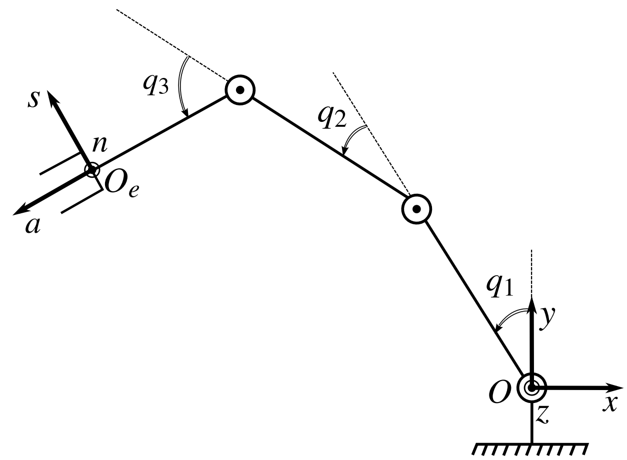

Fig. 3. A schematic view of the robot manipulator with the joint variables and the main frames.

B. Dynamics

Consider Fig. 4, where $m_i,\ I_i,\ l_{c_i}$, are the mass, the inertia and the position of the center of mass of the i-th link. The

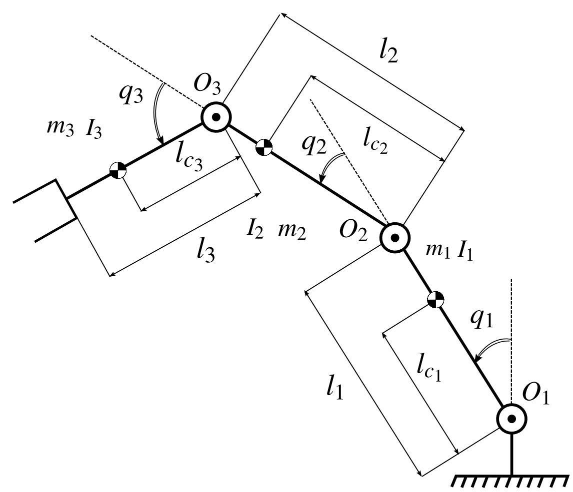

Fig. 4. A schematic view of the dynamical robotic system.

dynamics of the robot can be written in the joint space, by using the Lagrangian approach, as

$$B(q)\ddot{q} + n(q,\dot{q}) = \tau \tag{2}$$

$$n(q,\dot{q}) = C(q,\dot{q})\dot{q} + F_v\dot{q} + F_s sgn(\dot{q}) + g(q) \tag{3}$$

where $B(q)\in\mathbb{R}^{3\times3}$ is the inertia matrix, $C(q,\dot{q})\in\mathbb{R}^{3\times3}$ represents centripetal and Coriolis torques, $F_v\in\mathbb{R}^{3\times3}$ is the viscous friction matrix, $F_s\in\mathbb{R}^{3\times3}$ is the static friction matrix,

$g(q) \in \mathbb{R}^3$ is the vector of gravitational torques and $\tau \in \mathbb{R}^3$ represents the motors torques.

III. Problem Formulation

A. Inverse Dynamics Approach

In this paper, in order to reduce the nonlinear MIMO robotic system to a linear system, we use the so-called *Inverse Dynamics Control* approach [2]. The inverse dynamics of the robot manipulator can be written, in the joint space, as a nonlinear relationship between the plant inputs and the plant outputs, relying on (2)-(3), so that the control law can be expressed as

$$\tau = B(q)u + \hat{n}(q,\dot{q}) \tag{4}$$

where u is an auxiliary control variable. Note that the identified $B(q)$ coincides with the actual one, while $\hat{n}$ is an estimate of n, which does not necessarily coincide with n [22]. By applying the feedback linearization to the system (2)-(3), one obtains

$$\ddot{q} = u - \eta(q,\dot{q}) \tag{5}$$

where $\eta(q,\dot{q})$ takes into account the modelling uncertainties and external disturbances. In this way, the original MIMO system is reduced to three SISO decoupled systems, in which the state vector is $x_i = [x_{1_i} \; x_{2_i}]^T = [q_i \; \dot{q}_i]^T$, and η_i is the matched uncertainty such that

$$\begin{cases} \dot{x}_{1_i}(t) = x_{2_i}(t) \\ \dot{x}_{2_i}(t) = u_i(t) - \eta_i(t) \end{cases} \tag{6}$$

which is a double integrator, and where $\dot{x}_{2_i} = \ddot{q}_i$ represents the acceleration of the i-th joint. For the sake of simplicity, in the following subsections, the control law is designed relying on the SISO system modelling a single joint, and the subscript i is omitted. A law with the same structure is applied to each joint.

B. Preliminary Issues

Since any joint turns out to be modelled by (6), the system to control is a constrained linear SISO system of the form

$$\dot{x}(t) = Ax(t) + B(u(t) + \eta(t)) \tag{7}$$

where $x \in \mathbb{R}^2$ is the state vector, $u \in \mathbb{R}$ is the current control variable, and $\eta \in \mathbb{R}$ represents the external disturbances affecting the system. Moreover, $A \in \mathbb{R}^{2\times 2}$, and $B \in \mathbb{R}^2$. We also assume that the state variables are restricted to fulfill the following constraint

$$x \subset \mathcal{X} \tag{8}$$

where $\mathcal{X}$ is a compact set containing the origin as an interior point, while the control variable is such that

$$|u| \leq u_{max} \tag{9}$$

with u_{max} the limits of the actuators. Note that the limits could be considered different for each actuator. The uncertainty term η is also bounded such that

$$\eta \subset \mathcal{D} \tag{10}$$

where $\mathcal{D}$ is a compact set containing the origin with known $\mathcal{D}^{\sup} \equiv \sup_{\eta \in \mathcal{D}}\{|\eta|\}$.

C. Problem Statement

We are now in a position to be able to formulate the control problem to solve. Given the robot system described in Section II, the aim of the control system to be designed is to make the robot system perform a simple task of reference tracking. In the following section, a functional architecture including a MPC module and an ISM controller is designed to solve the problem.

IV. Model Predictive Control and Integral Sliding Mode: The Control Strategy

MPC is designed in order to obtain an optimal solution to the control problem. Moreover, in order to reduce the uncertainty terms affecting the system, an ISM controller is introduced. The whole control variable $u(t)$ is chosen as follows

$$u(t) = u_{MPC}(t) + u_{ISM}(t) \tag{11}$$

where u_{MPC} and u_{ISM} are generated by the MPC controller and the ISM controller, respectively. The ISM controller is based on the continuous-time model of the system and on the signal generated by the MPC controller, which, in turn, is based on the discrete-time model of the original system.

A. The Considered Control Scheme

In Fig. 5 the proposed control scheme for the considered robot is illustrated. This scheme includes three control loops.

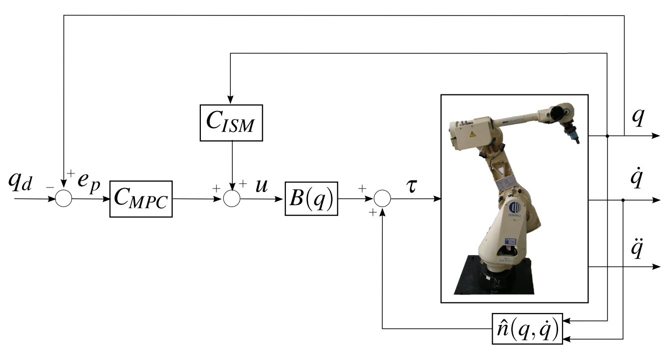

Fig. 5. The proposed control scheme with the inverse-dynamics based feedback linearized system, the ISM controller and the MPC of the outer loop.

The first loop is based on the Inverse Dynamics approach, described in the previous section. The second loop is closed relying on the ISM controller C_{ISM} which computes $u_{ISM} \in \mathbb{R}^3$ and rejects the unavoidable modelling uncertainties and external disturbances affecting the system after the inverse dynamics feedback linearization. The third loop is designed to implement the MPC based controller C_{MPC} which computes the control $u_{MPC} \in \mathbb{R}^3$ combined with $u_{ISM} \in \mathbb{R}^3$ so as to optimize the control performance and comply with the constraints. The position error of the controlled system, which is the input to Controller C_{MPC}, is defined as $e_p = q - q_d$, q_d being the desired angular reference.

B. Integral Sliding Mode Controller

The ISM control provides robustness to the scheme in front of a significant class of uncertainties, and enforces sliding modes of the controlled system since the initial time instant. This method is based on the existence of an *ideal system* with a known nonlinear plant and a properly designed feedback control, and on a discontinuous control to remove unavoidable modelling uncertainties and external disturbances. Considering the dynamic system (6), we assume that the so-called sliding variable $s \in \mathbb{R}$, according to [20], is defined as follows

$$s(x(t)) = [m\ 1]\left(x(t) - x(t_0) - \int_{t_0}^{t} [x_2(\zeta)\ u_{MPC}(\zeta)]^T d\zeta\right) \tag{12}$$

with $s(x(t)) = 0$ the associate integral sliding manifold, and m a positive constant. Now, we consider the control law expressed as follows

$$u_{ISM} = -U_{max}\,\mathrm{sgn}(s) \tag{13}$$

where $U_{max} > 0$ is suitably chosen in order to enforce the sliding mode. As shown in [20], the equivalent control, obtained via a first order liner filter with the real discontinuous control (13) as its input, can be used in order to avoid high frequency switching of the component of the control torque. The effect of the ISM control law is that of rejecting the uncertainty of the system (6) so as to obtain

$$\begin{cases} \dot{x}_1(t) = x_2(t) \\ \dot{x}_2(t) = u(t) \end{cases} \tag{14}$$

which is a double integrator without disturbances affecting the system. Note that the ISM control cannot violate the state constraints due to the fact that the sliding variable also depends on the MPC control law.

C. Linear Model Predictive Controller

By virtue of the rejection of matched uncertainties and external disturbances through the use of the ISM controller, the MPC controller must not consider uncertainty and can be synthesized on the nominal model. In particular, state and input constraints are satisfied by the real system without imposing any conservativeness in the optimization problem.

The MPC controller is designed for system (14) which is the result of the joint application of the Inverse Dynamics and ISM control. The adopted MPC controller is based on the solution of the so-called Finite-Horizon Optimal Control Problem (FHOCP) which consists in minimizing, at any sampling time t_k, a suitably defined cost function with respect to the control sequence $u_{[t_k,t_{k+N-1}|t_k]} \equiv [u_0(t_k),\ u_1(t_k), \ldots, u_{N-1}(t_k)]$, with $N \geq 1$ being the prediction horizon. In our case, the cost function to minimize with respect $u_{[t_k,t_{k+N-1}|t_k]}$ is the following

$$\begin{aligned} & J(e_{[t_k,t_{k+N-1}|t_k]}, w_{[t_k,t_{k+N-1}|t_k]}, N) = \\ & = \sum_{j=0}^{N-1} [e^T(t_{k+j}) Q e(t_{k+j}) + w^T(t_{k+j}) R w(t_{k+j})] + \\ & \quad + e^T(t_{k+N}) P e(t_{k+N}) \end{aligned} \tag{15}$$

with $e = x - \bar{x}$, $w = u - \bar{u}$, $\bar{x}$ and $\bar{u}$ being the reference values to reach and the corresponding control value of each joint of the robot manipulator, respectively. The cost function (15) is also subjected to the constraint on the state variables in (8) and

$$u_{MPC_{max}} = u_{max} - U_{max} \tag{16}$$

with u_{max} as in (9), and U_{max} introduced in the ISM control law (13). Moreover, Q and R are positive definite matrices, and P is the terminal state weight so as to ensure the stability of the controlled system [7]. This latter represents the solution to the *Lyapunov equation*

$$(A - BK_{LQ})^T P (A - BK_{LQ}) - P = -Q - K_{LQ}{}^T R K_{LQ} \tag{17}$$

where K_{LQ} is the control gain of a Linear-Quadratic (LQ) controller with the same cost function. The terminal state constraint is such that $e(t_{k+N}) \in \mathcal{X}_f$, with

$$\mathcal{X}_f \equiv \{e|\ e^T P e \leq \sigma,\ |K_{LQ} e| < u_{MPC_{max}}\}, \quad \mathcal{X}_f \subseteq \mathcal{X} \tag{18}$$

containing the origin as an interior point and with σ being a positive real number. Then, according to the *Receding Horizon* strategy, the applied control law is the following

$$u_{MPC}(t) = K_{MPC}(e(t_k)), \quad t \in [t_k, t_{k+1}) \tag{19}$$

where

$$K_{MPC}(e(t_k)) \equiv u_0^o(t_k) \tag{20}$$

with $u_0^o(t_k)$ the first value at t_k of the optimal control sequence, obtained by solving the FHOCP. Since the matched uncertainties are rejected by the ISM control, the linear MPC can be designed on a system with no disturbances and tightened constraints are not required. This fact, considering also the low computational burden required by the ISM control and the feedback linearization from the original MIMO system to three decoupled SISO systems, implies low computational load for the whole proposed controller.

V. Simulation Results

In this section the previously proposed control strategy is applied in simulation to the model of the considered robot manipulator, i.e. a COMAU SMART3-S2 anthropomorphic industrial robot. Note that the model has been identified on the basis of real data through experimental tests, so that the simulation environment is quite realistic. Moreover, in order to better emulate a realistic robot, random noise $\eta = [\eta_1\ \eta_2\ \eta_3]^T$ is injected to the acceleration of the joints, with the following bounds registered during experimental tests [23]

$$|\eta_1| \leq 20 \tag{21}$$
$$|\eta_2| \leq 30 \tag{22}$$
$$|\eta_3| \leq 85 \tag{23}$$

We have considered only three joints, as previously mentioned (see Fig. 2). They have some limits in terms of maximum reachable angle and in terms of maximum axis acceleration, as reported in Table I. Note that also

TABLE I
ACTUATORS LIMITS.

i	$\lvert q_{i_{max}} \rvert$	$\lvert u_{i_{max}} \rvert$
1	1.83	145
2	2.7	250
3	2.18	350

these values have been evaluated on the actual robot through experimental tests. Moreover, since τ depends on the MPC and ISM controllers (see Eq. (4)), it is also possible to comply with constraints on τ by suitably sizing the constraints on u_i, $i = 1,2,3$. The main goal is to make each joint following

TABLE II
ISM CONTROL PARAMETERS.

i	m_i	U_{max_i}
1	10	20
2	10	30
3	10	85

a reference position, moving from the point $(q_{1_0}, q_{2_0}, q_{3_0}) = (0,0,0)$ to $(q_{1_f}, q_{2_f}, q_{3_f}) = (\pi/6, \pi/4, -\pi/4)$, with a step signal as input. According to the proposed control strategy, on one hand, the ISM based control loop is defined such that the integral sliding variable is chosen as in (12) and the control parameters are those reported in Table II.

TABLE III
MPC CONSTRAINTS.

i	$\lvert q_{i_{max}} \rvert$	$\lvert u_{MPC_{i_{max}}} \rvert$
1	1.83	125
2	2.7	220
3	2.18	265

On the other hand, the MPC control is implemented, choosing the matrices in the cost function as $Q = \text{diag}(100\ 0.01)$ and $R = 0.00001$. We also consider the terminal state weight equal to

$$P = \begin{bmatrix} 1653.9 & 63.2 \\ 63.2 & 5.1 \end{bmatrix} \tag{24}$$

Moreover, the sampling time of the simulation is chosen as T_s =0.001 s, while the sampling time of the MPC control loop is T_{MPC} =0.005 s, with the prediction horizon $N = 3$. In order to fulfill the constraints reported in Table I, the constraints imposed to the MPC are smaller than the actuators limits and they are reported in Table III.

Fig. 6 shows the position of each joint and the orientation angle of the end-effector when only the MPC control is applied without rejecting the uncertain terms through the ISM control approach, Fig. 7 shows the results when ISM control loop is considered, while Fig. 8 shows the evolution of the control variable u in the same case.

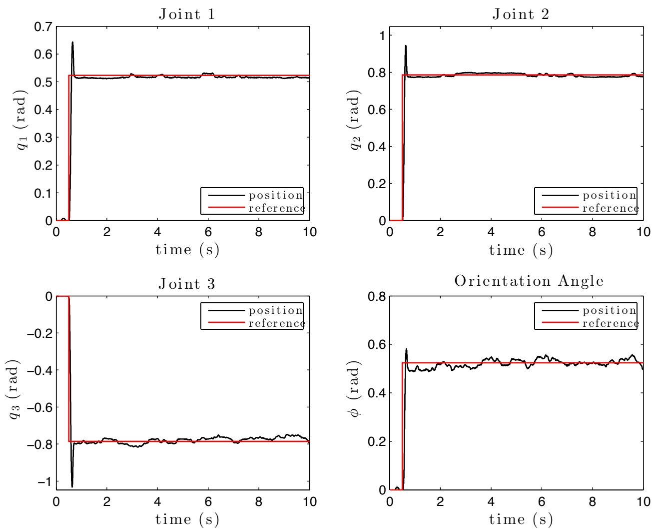

Fig. 6. Position evolution (solid black line), and reference step signal (dotted red line) for joints 1,2,3, respectively, when the ISM controller is absent.

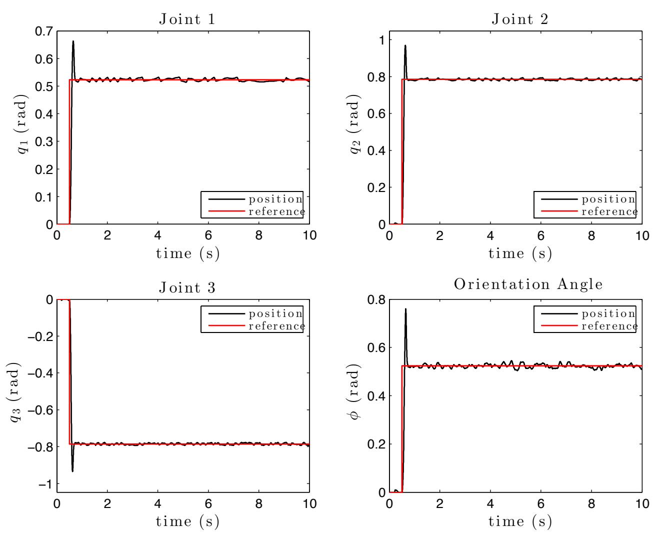

Fig. 7. Position evolution (solid black line), and reference step signal (dotted red line) for joints 1,2,3, respectively, when the ISM controller is present.

The root mean square error, computed as

$$e_{p_{RMS}} = \sqrt{\frac{1}{M}\sum_{j=1}^{M} \|e_{p_j}\|^2} \tag{25}$$

where M is the number of sampled data, results in being $e_{p_{RMS}} = 8.0616 \times 10^{-4}$ rad with ISM, and $e_{p_{RMS}} = 1.2 \times 10^{-3}$ rad without ISM.

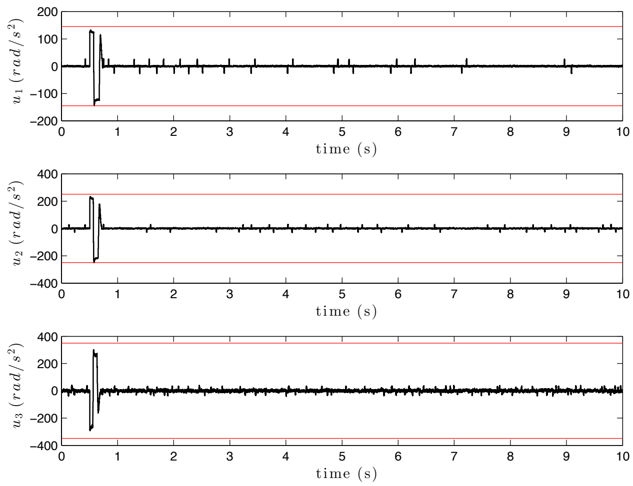

Fig. 8. The adopted control variable evolution (solid black line), and control constraints (solid red line), when the ISM controller is present.

It is evident that the performance are better in the case with ISM internal control loop, but apart from, what is relevant is that state and control constraints are respected by relying on decentralized linear MPC even if the robotic system is nonlinear and coupled.

VI. Conclusions

A robust hierarchical multi-loop control scheme aimed at solving motion control problems for robot manipulators has been presented in this paper. The objective was to ensure the optimal evolution of the controlled system in the respect of state and input constraints, while keeping the computational complexity to a minimum, in order to make the proposal really usable in practice. The scheme is designed by suitably combining a basic Inverse Dynamics feedback linearizing approach with Integral Sliding Mode control, and Model Predictive Control. The hierarchical application of the foregoing methodologies allows one to transform the nonlinear MIMO robotic system into a set of linearized decoupled SISO systems, insensitive to the matched uncertainties presence. These latter are controlled by solving a low complexity constrained optimal control problem. The assessment of the performance of the proposed control scheme is carried out in simulation relying on a realistic model of an industrial COMAU SMART3-S2 robot manipulator, identified on the basis of experimental tests.

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